# Quantitative Approaches to Political Science Research

# Quantitative Approaches

- We've covered:
  - Mean, median, mode
  - Variance, standard deviation, standard error
  - $\chi^2$ tests, t-tests, and Pearson's correlation coefficients
- Today we'll cover:
  - Bivariate and multivariate linear regression
  - Time permitting, maximum likelihood approaches (logit/probit)

# Quantitative Approaches

| Variables | (1) *CR* | (2) *IJE* | (3) *IJE-CR* | (4) *Macro* | (5) *Firm* | (6) *Firm* | (7) *Firm All* | (8) *Fama McBeth* | (9) *Firm All* |
|---|---|---|---|---|---|---|---|---|---|
| *CR* | −0.021*** | | −0.016*** | −0.018*** | −0.014 | −0.018** | −0.018** | −0.019*** | −0.020*** |
| | (0.007) | | (0.003) | (0.004) | (0.009) | (0.007) | (0.007) | (0.002) | (0.001) |
| *IJE* | | 0.109* | 0.095** | 0.100*** | 0.119* | 0.131* | 0.135** | 0.132*** | 0.126*** |
| | | (0.059) | (0.042) | (0.030) | (0.066) | (0.066) | (0.064) | (0.005) | (0.006) |
| *PROF* | | | | | −0.002 | −0.019 | −0.036 | −0.038*** | −0.005 |
| | | | | | (0.016) | (0.026) | (0.036) | (0.007) | (0.007) |
| *SZ* | | | | | 0.006* | 0.007* | 0.007* | 0.008*** | 0.006*** |
| | | | | | (0.003) | (0.004) | (0.004) | (0.000) | (0.000) |
| *COLAT* | | | | | 0.118*** | 0.125*** | 0.115*** | 0.115*** | 0.126*** |
| | | | | | (0.018) | (0.017) | (0.016) | (0.006) | (0.005) |
| *RD* | | | | | −0.070 | −0.069 | −0.056 | −0.067*** | −0.057*** |
| | | | | | (0.073) | (0.080) | (0.096) | (0.011) | (0.022) |
| *LIQ* | | | | | −0.005*** | −0.005*** | −0.007*** | −0.007*** | −0.009*** |
| | | | | | (0.001) | (0.001) | (0.002) | (0.000) | (0.000) |
| *TAX* | | | | | −0.038*** | −0.034*** | −0.034*** | −0.035*** | −0.045*** |
| | | | | | (0.012) | (0.012) | (0.012) | (0.002) | (0.004) |
| *CAPEX* | | | | | 0.067 | 0.059 | 0.113 | 0.114*** | 0.042*** |
| | | | | | (0.066) | (0.059) | (0.078) | (0.020) | (0.016) |
| *DCPSF* | | | | −0.010 | | −0.020 | −0.021 | −0.023*** | −0.019*** |
| | | | | (0.015) | | (0.017) | (0.016) | (0.005) | (0.002) |
| *MCAP* | | | | 0.008 | | 0.017* | 0.018* | 0.022*** | 0.022*** |
| | | | | (0.007) | | (0.010) | (0.010) | (0.004) | (0.002) |
| *VOL* | | | | | | | −0.092*** | −0.096*** | −0.127*** |
| | | | | | | | (0.028) | (0.009) | (0.015) |
| *ASLF* | | | | | −0.009 | | | | |
| | | | | | (0.047) | | | | |
| Constant | 0.169*** | 0.112*** | 0.160*** | 0.159* | 0.093** | 0.095 | 0.118 | 0.103*** | 0.109** |
| | (0.026) | (0.020) | (0.020) | (0.082) | (0.041) | (0.073) | (0.076) | (0.021) | (0.043) |
| Observations | 303,270 | 189,570 | 189,290 | 181,109 | 131,176 | 126,004 | 100,703 | 100,703 | 100,703 |
| R-squared | 0.129 | 0.127 | 0.139 | 0.138 | 0.218 | 0.221 | 0.227 | 0.239 | 0.268 |
| Industry dummy | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year dummy | YES | YES | YES | YES | YES | YES | YES | YES | YES |

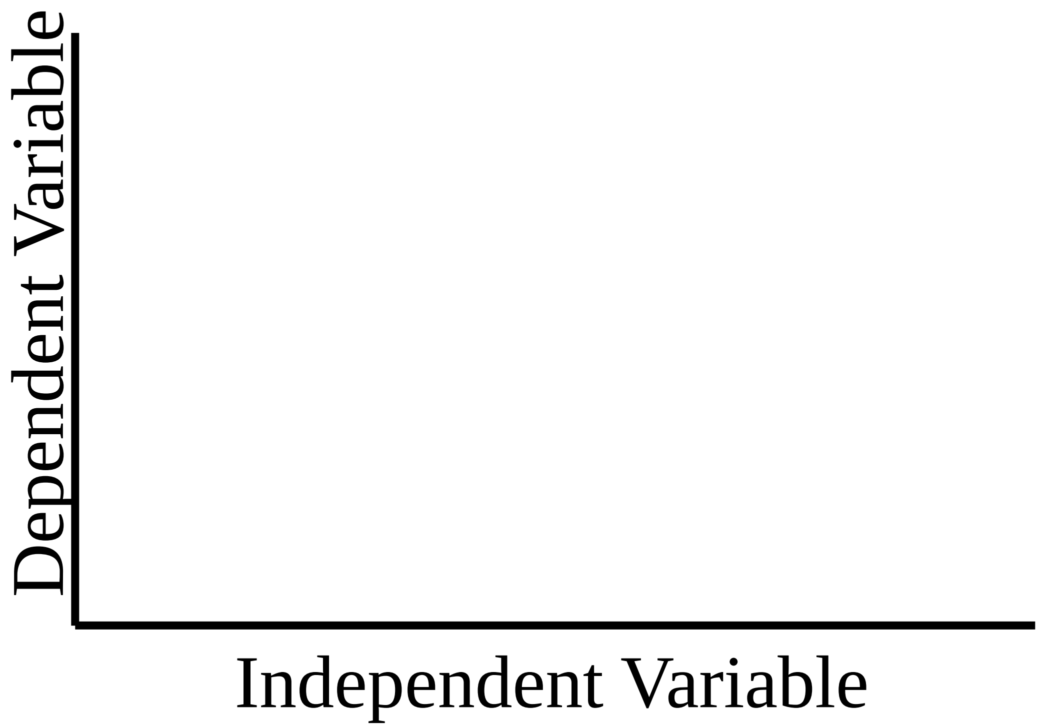
# Quantitative Approaches

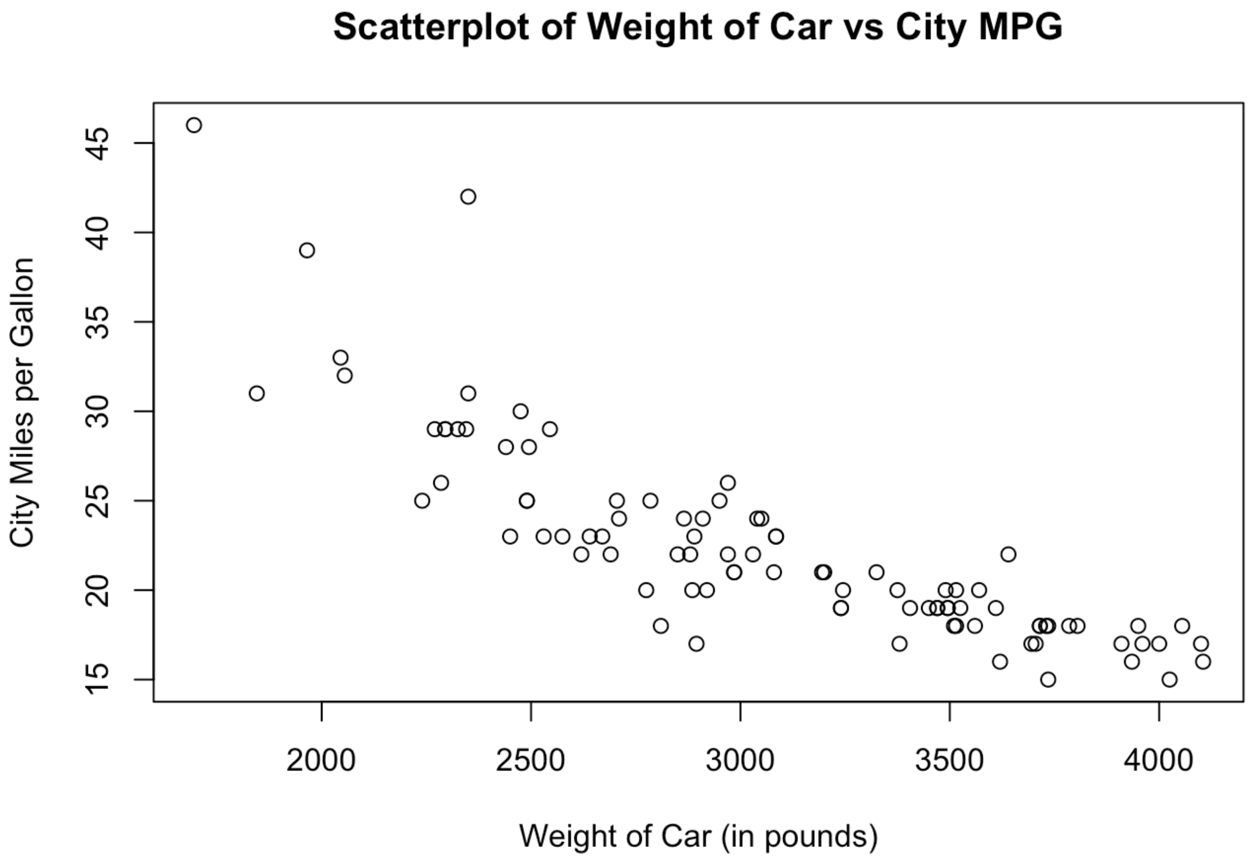
Table 8.1 Variable types and appropriate bivariate hypothesis tests

| | | Independent variable type | |
|---|---|---|---|
| | | Categorical | Continuous |
| Dependent variable type | Categorical | *tabular analysis* | probit/logit (Ch. 12) |
| | Continuous | *difference of means*; regression extensions (Ch. 11) | *correlation coefficient*; two-variable regression model (Ch. 9) |

*Note*: Tests in italics are discussed in this chapter.

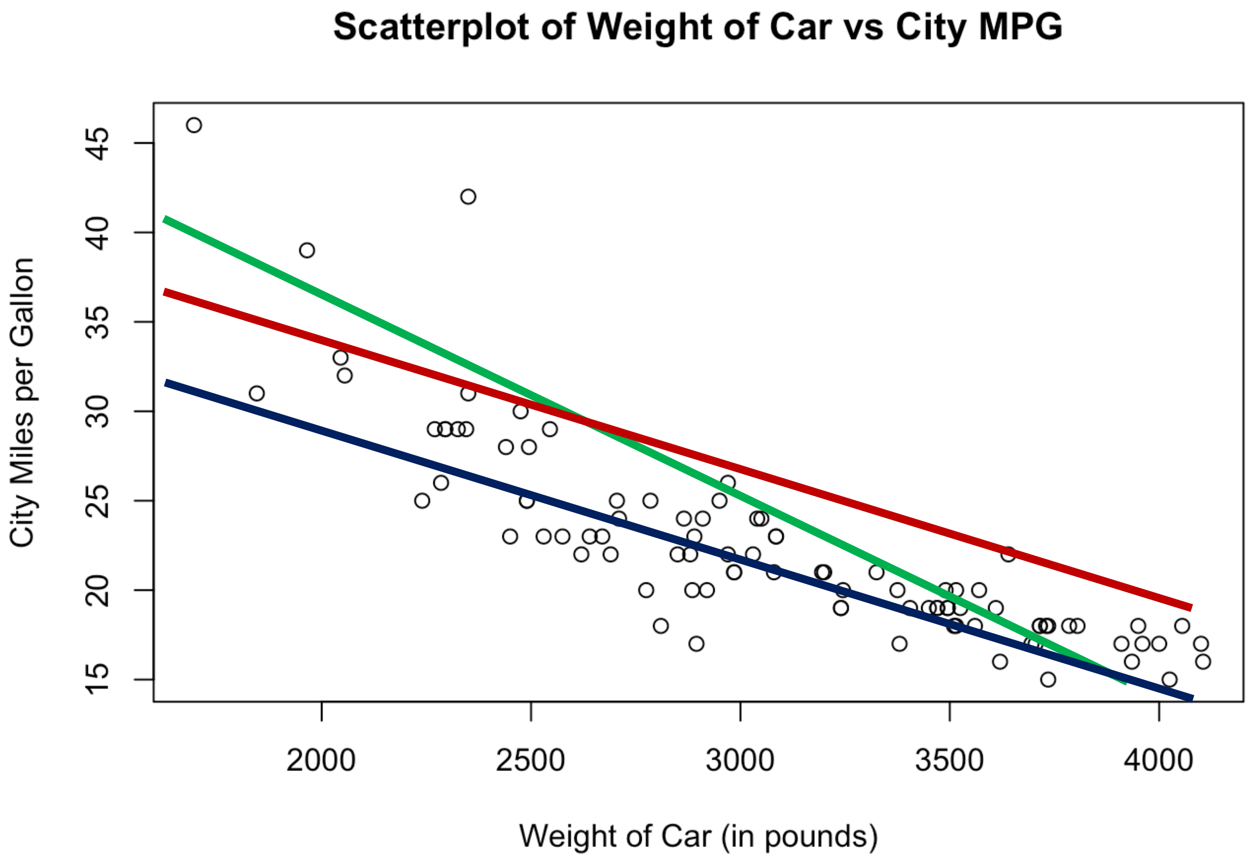
# Linear Regression



# Linear Regression

- For linear relationships…
- y=mx+b
- Where to fit this line?
- We require a systematic means to find the line of best fit
    - Least squares approach



# Linear Regression

- We need to move past the y=mx+b formulation

$$y_i = \alpha + \beta x_i + u_i$$

- $y_i$: dependent variable
- $\alpha$: Y intercept
- $\beta$: slope coefficient
- $x_i$: independent variable
- $u_i$: residual

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# Linear Regression

- We need to move past the y=mx+b formulation

$$y_i = \alpha + \beta x_i + u_i$$

- $\beta$: slope coefficient
  - Consider this as the effect of your independent variable on the dependent variable (Y=β * X)
- $u_i$: residual
  - Residual here is synonymous with error; this is the degree of deviation from the line of best fit and the observed value

# Linear Regression

- We need to move past the y=mx+b formulation

$$y_i = \alpha + \beta x_i + u_i$$

- We also need to be conscious that this is the population equation
- This is the data generating process (DGP) in the world, not necessarily in our sample

# Linear Regression

- We need to move past the y=mx+b formulation

$$y_i = \hat{\alpha} + \hat{\beta} x_i + \hat{u}_i$$

- We also need to be conscious that this is the population equation
- This is the data generating process (DGP) in the world, not necessarily in our sample
- When are discussing estimated values, we put a little hat on the variables – alpha hat, beta hat, etc.
- This is the sample regression equation

# Linear Regression

- We need to move past the y=mx+b formulation

$$y_i = \hat{\alpha} + \hat{\beta} x_i + \hat{u}_i$$

- Because the α, β, and $\hat{u}$ values are not *known*, but rather *estimated*, they get hats
- This signals that we don't know these values, and we likely cannot know these values, but we estimate a range of likely values within which the population ('true') value lies – recall confidence intervals

# Linear Regression

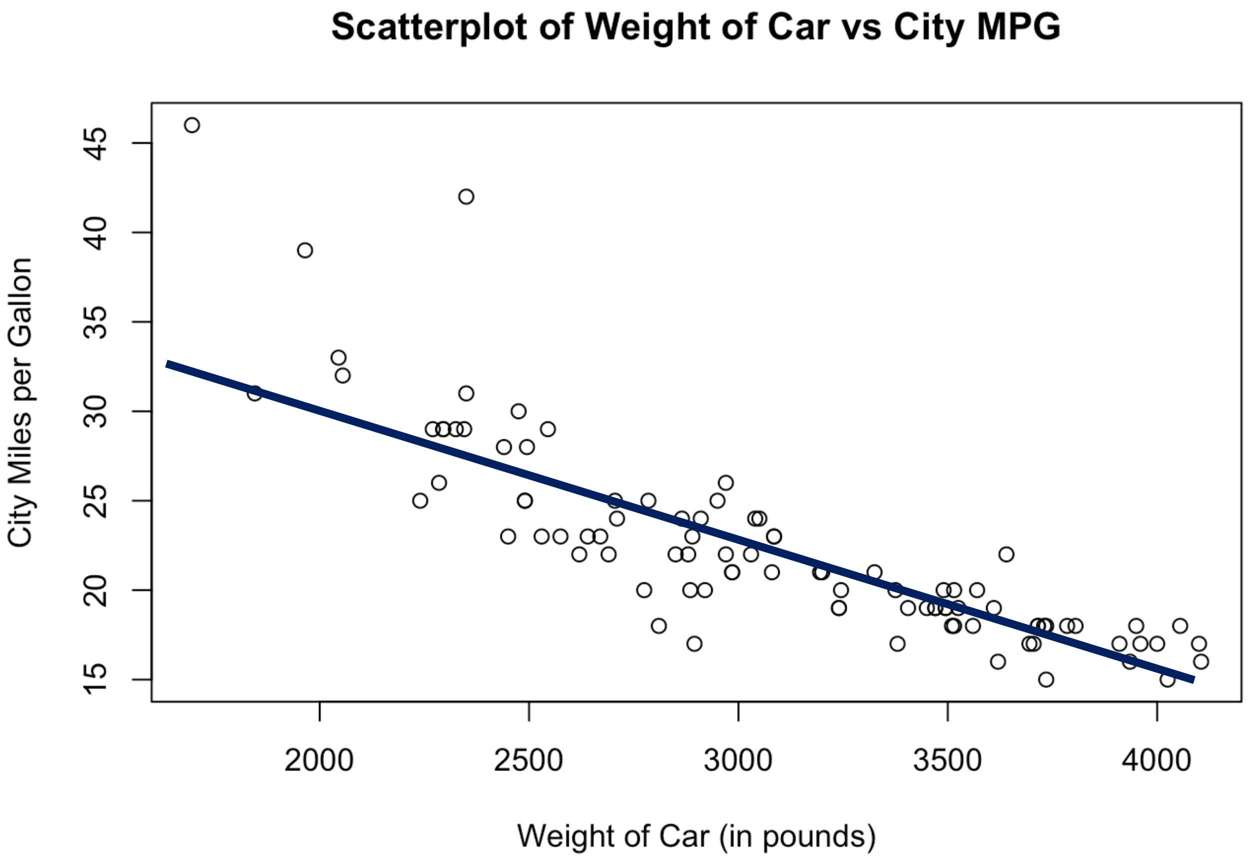
$$y_i = \hat{\alpha} + \hat{\beta} x_i + \hat{u}_i$$

- Recall the difference between stochastic and systematic variation
- Both operate in this equation
- We can dichotomize $\hat{u}_i$ into two components

$$\hat{u}_i = \varepsilon_i + u_i$$

- Where $\hat{u}_i$ are our observed residuals, $\varepsilon_i$ is the unmodelled systematic variation, and $u_i$ is the remaining random (stochastic) variation

# Linear Regression



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$$\hat{u}_i = \varepsilon_i + u_i$$

- We will always have some level of $\hat{u}_i$ due to both stochastic and systematic variation, no matter how many IVs we add

# Linear Regression

$$y_i = \hat{\alpha} + \hat{\beta}x_i + \hat{u}_i$$

- Recall the difference between stochastic and systematic variation
- Both operate in this equation
- We can dichotomize $\hat{u}_i$ into two components

$$\hat{u}_i = \varepsilon_i + u_i$$

- As we'll see later, it is not always beneficial to add more IVs to decrease $\hat{u}_i$

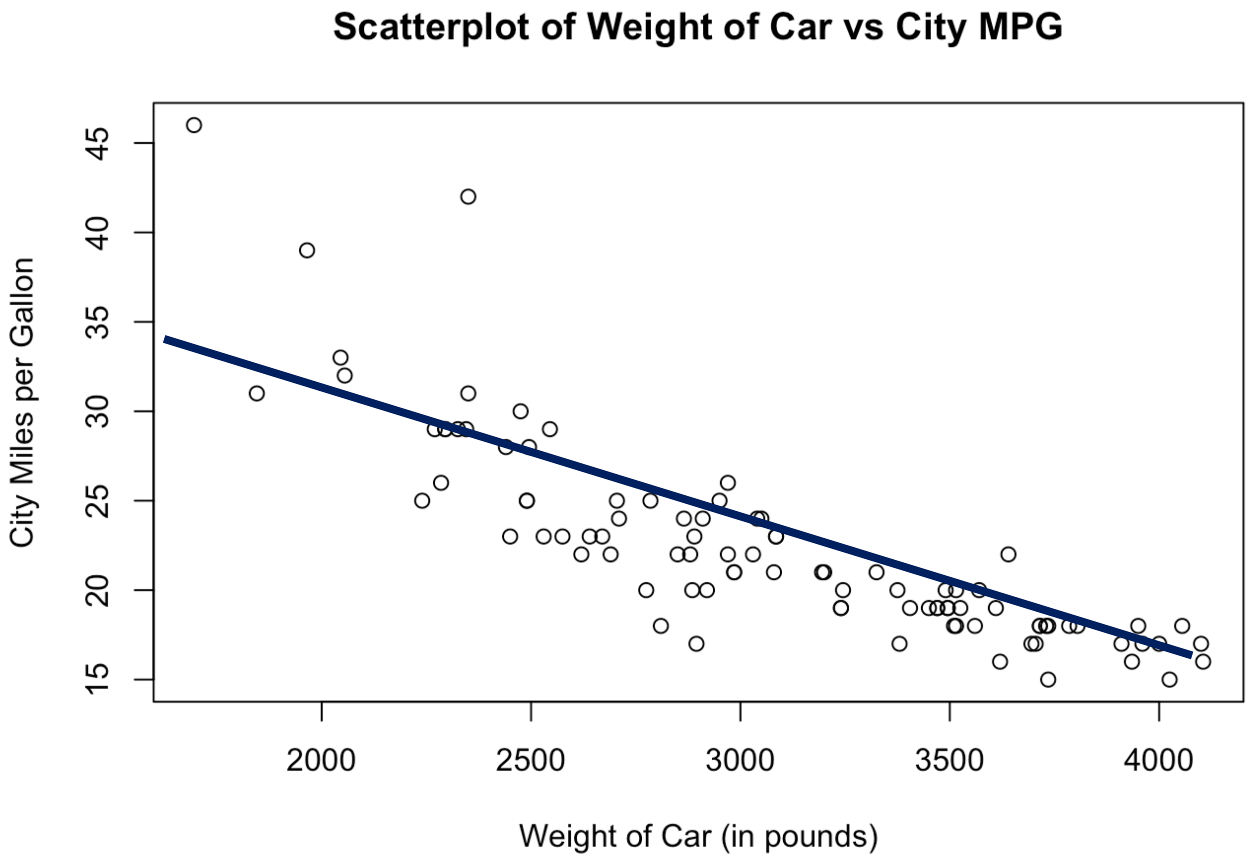
# Linear Regression

$$y_i = \hat{\alpha} + \hat{\beta}x_i + \hat{u}_i$$

- What do we really care about in this equation?
- We want to find $\hat{\beta}$ as this is the estimated effect of our independent variable(s) on the observed outcome (DV)
- But we also need to know where this effect begins ($\hat{\alpha}$) as well as our degree of confidence about our estimates ($\hat{u}_i$)

# Linear Regression

- Returning to the scatterplot
- We want to find the line of best fit
- This is determined by the line that minimizes distance between our observations and the linear line



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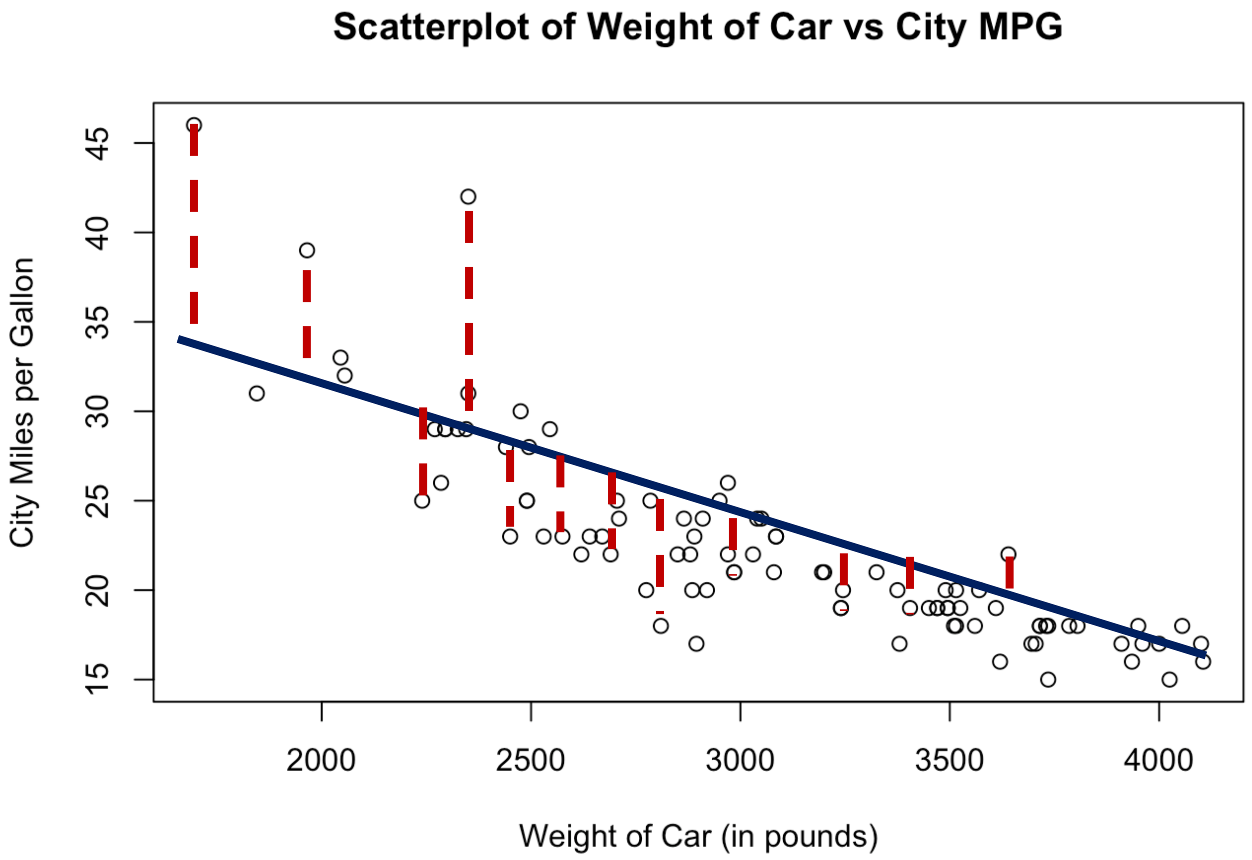
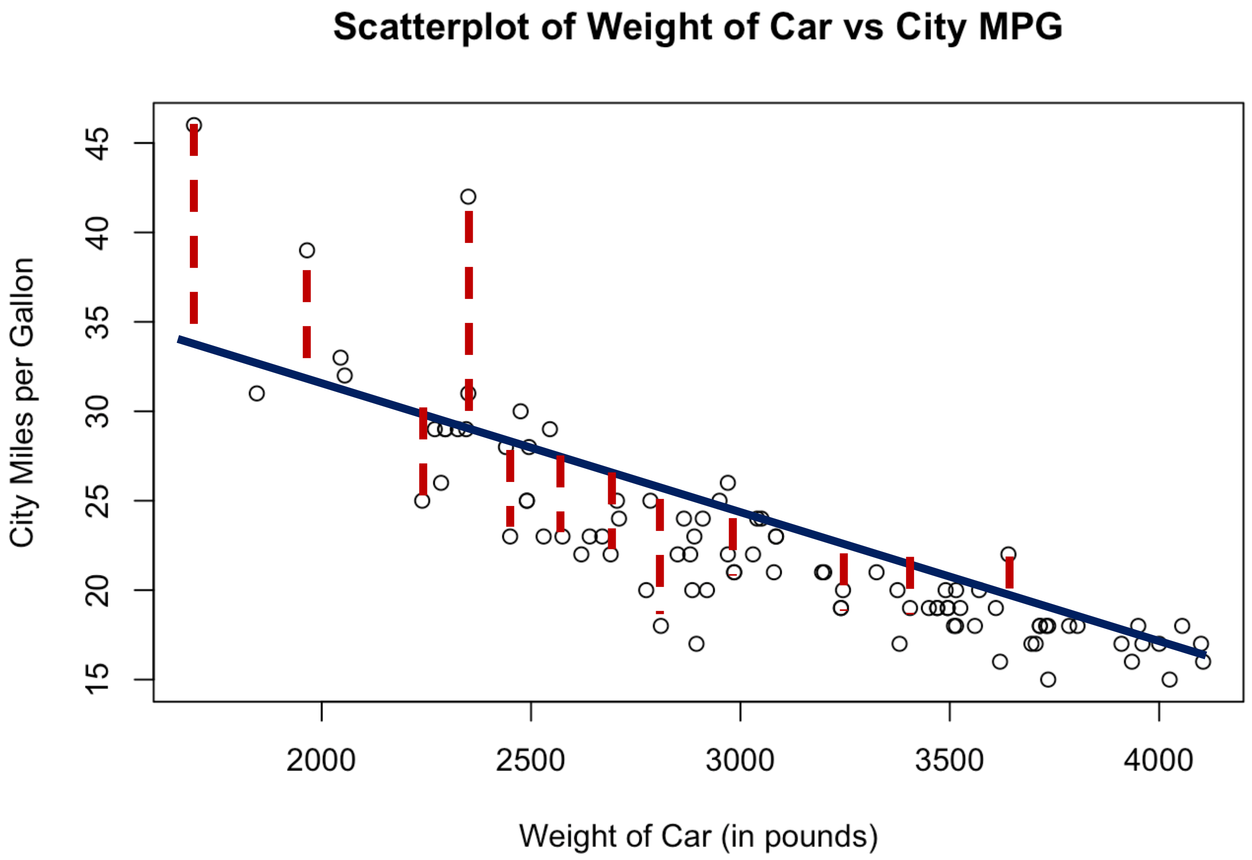


# Linear Regression

- This is performed via the two equations below

- $\hat{\beta} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}$

- $\alpha = \bar{y} - \hat{\beta}\bar{x}$



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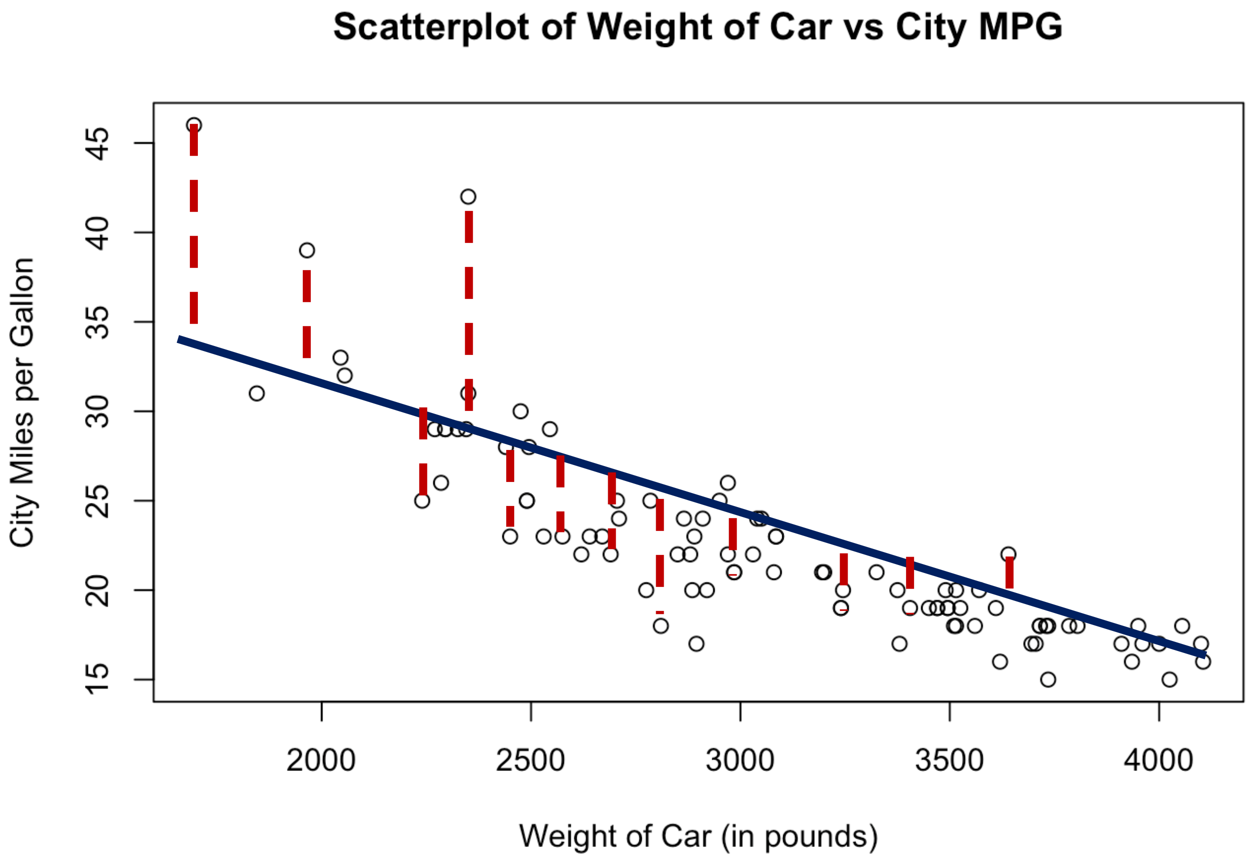
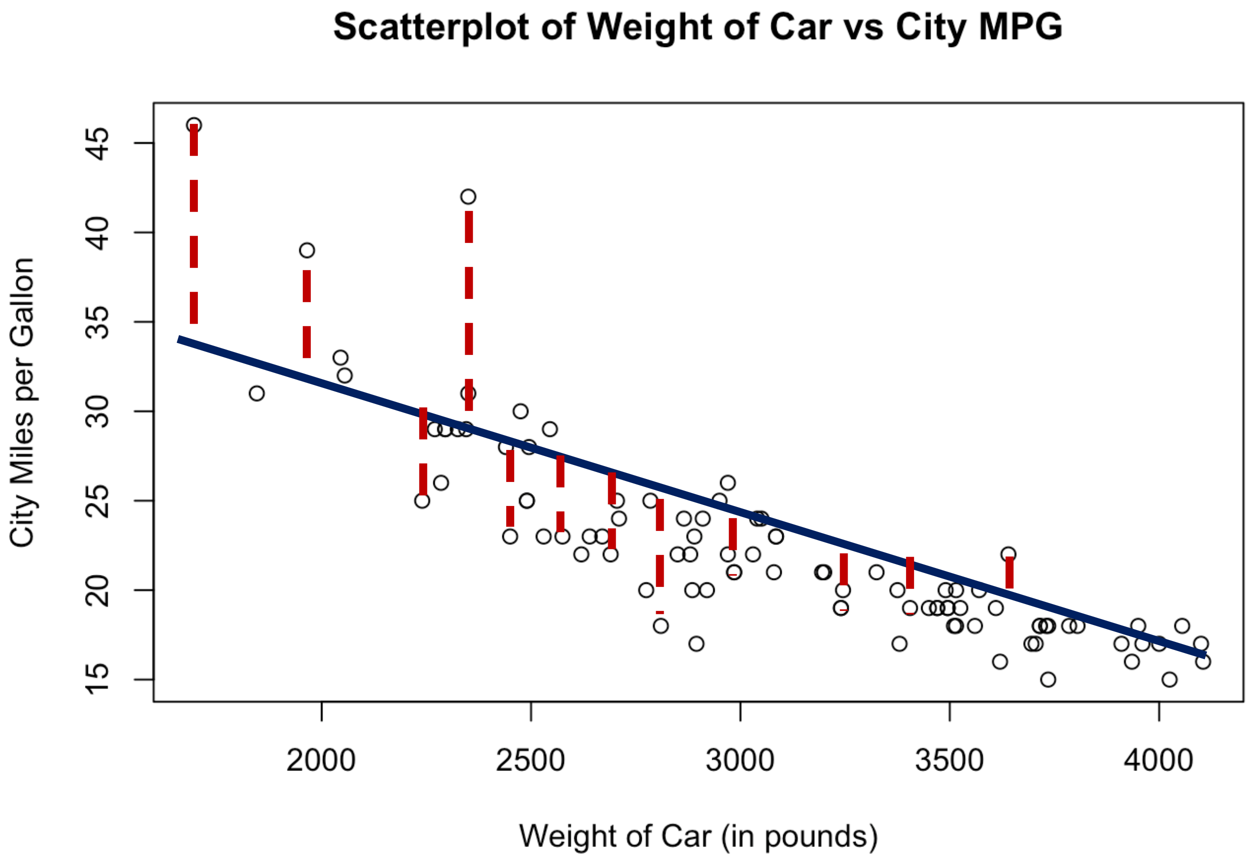


# Linear Regression

- This is performed via the two equations below

- $\hat{\beta} = \frac{\sum_{i=1}^{n} \cancel{(x_i - \bar{x})}(y_i - \bar{y})}{\sum_{i=1}^{n} \cancel{(x_i - \bar{x})}(x_i - \bar{x})}$

- $\alpha = \bar{y} - \hat{\beta}\bar{x}$



# Linear Regression

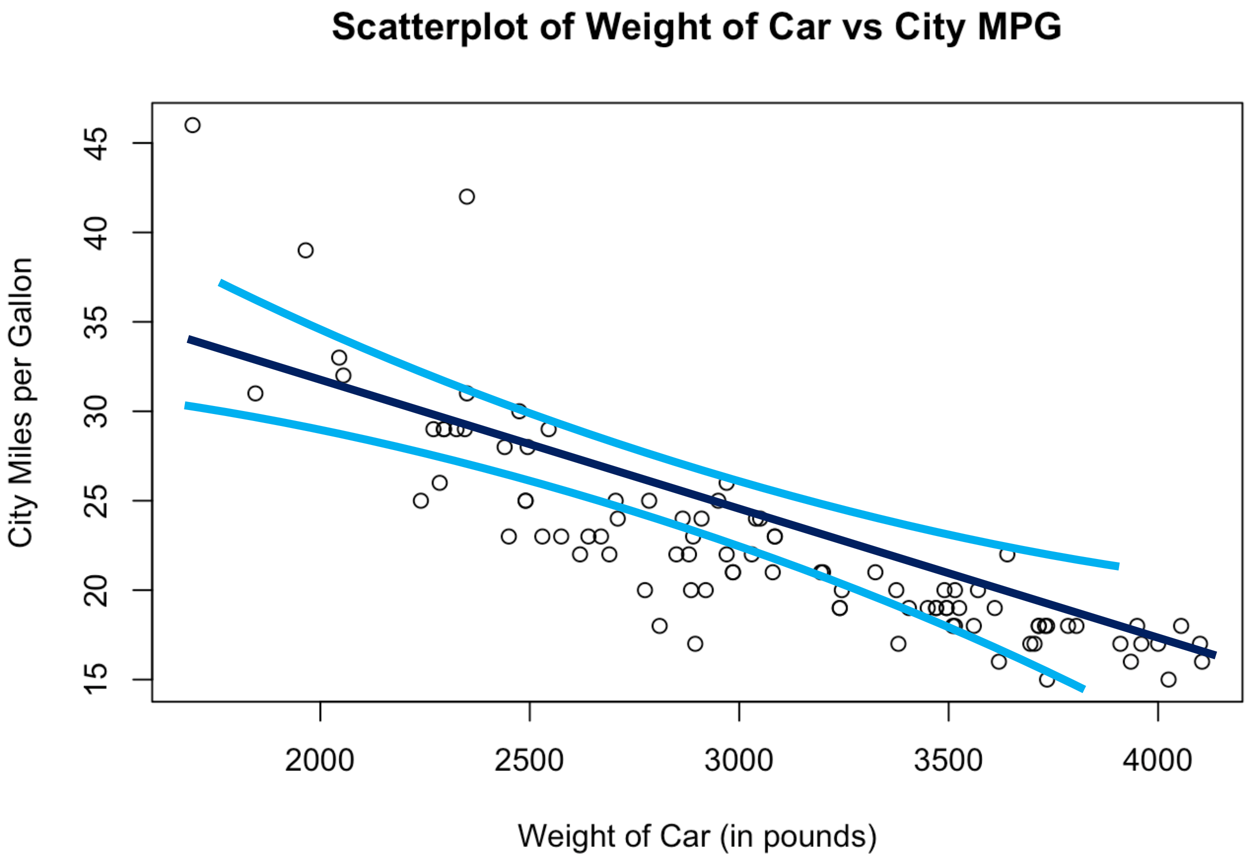
- Once we have our coefficient estimates, we calculate the standard error of the β and α coefficients through the following equations

$$\widehat{SE}\left(\hat{\beta}\right) = \sqrt{\frac{\hat{\sigma}^2}{\Sigma_{\mathrm{i=1}}^{n}(x_i - \bar{x})^2}}$$

$$\hat{\sigma}^2 = \frac{1}{n-k-1} \cdot \sum_{i=1}^{n} \hat{u}_i^2$$

# Linear Regression

- In doing, we can construct a confidence interval about our regression estimate
- Generally, 95%
- We are 95% confident that the ‘true’ effect of X on Y falls within this range – both slope and intercept



# Linear Regression

- This is called *Ordinary Least Squares (OLS)*
- The name derives from the process of finding the line that minimizes the square distances between the regression line and the observations
- This is also termed linear regression or least squares regression
- This process has several benefits as well as a number of restrictions

# Linear Regression: BLUE

- We use OLS because it is BLUE
  - The best, linear, unbiased estimator
- Best: Minimum variance between β and $\hat{\beta}$, and α and $\hat{\alpha}$, as the sample size approaches ∞
- Linear: Where the relationship under study is linear, we use a linear estimator
- Unbiased: Accurately estimates the regression coefficients ($\hat{\alpha}$, $\hat{\beta}$)

# Linear Regression: Gauss Markov Assumptions

- OLS has a number of assumptions/requirements
- These are known as the Gauss-Markov Assumptions

- The relationship under study must be linear in the population

# Linear Regression: Gauss Markov Assumptions

- OLS has a number of assumptions/requirements
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- Our data is randomly drawn from the population

# Linear Regression: Gauss Markov Assumptions

- OLS has a number of assumptions/requirements
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- The IVs are not perfectly correlated with one another
  - Non-collinearity

# Linear Regression: Gauss Markov Assumptions

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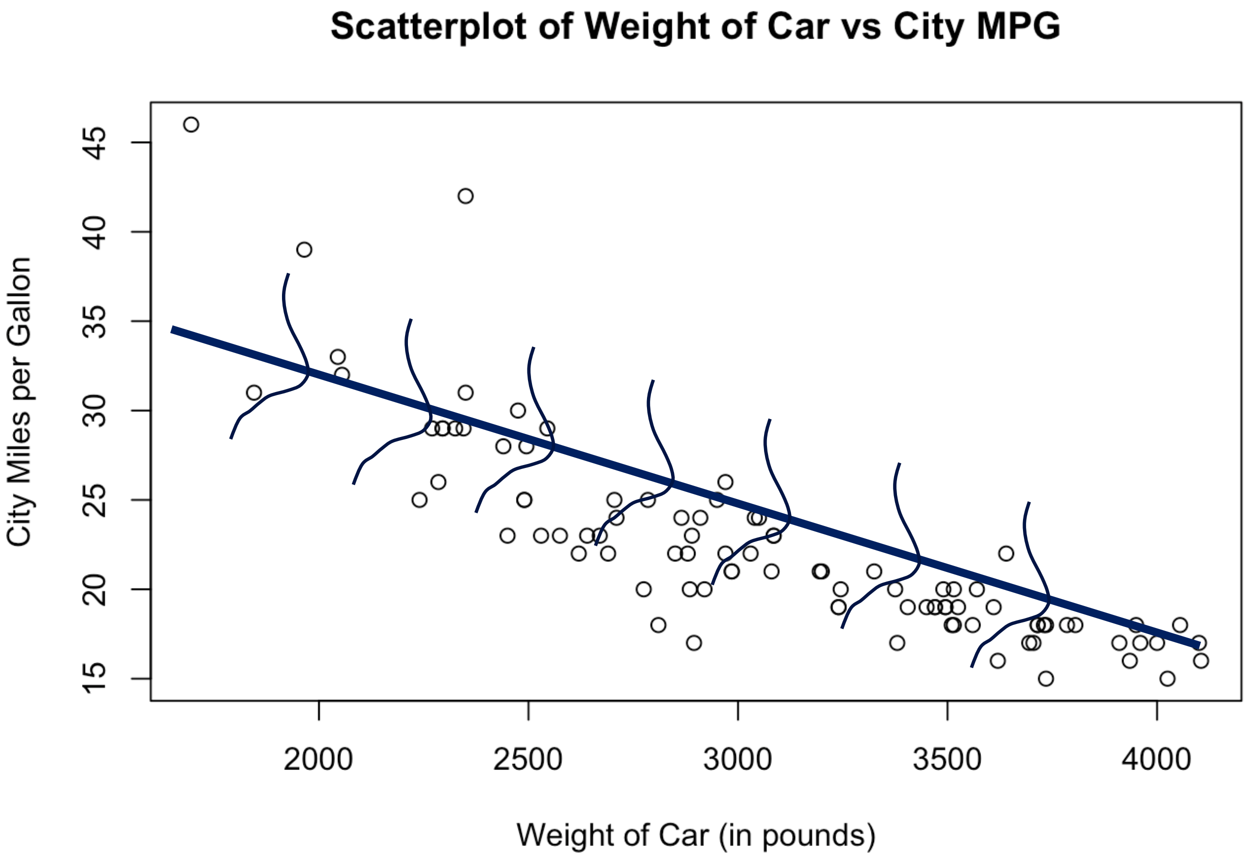
# Linear Regression: Gauss Markov Assumptions

- OLS has a number of assumptions/requirements
- These are known as the Gauss-Markov Assumptions

- The errors (residuals) are uncorrelated with each other, and the IVs, and with an expected value of 0
- $\text{cov}(u_i, u_j) = 0$
- $E(u_i) = 0$

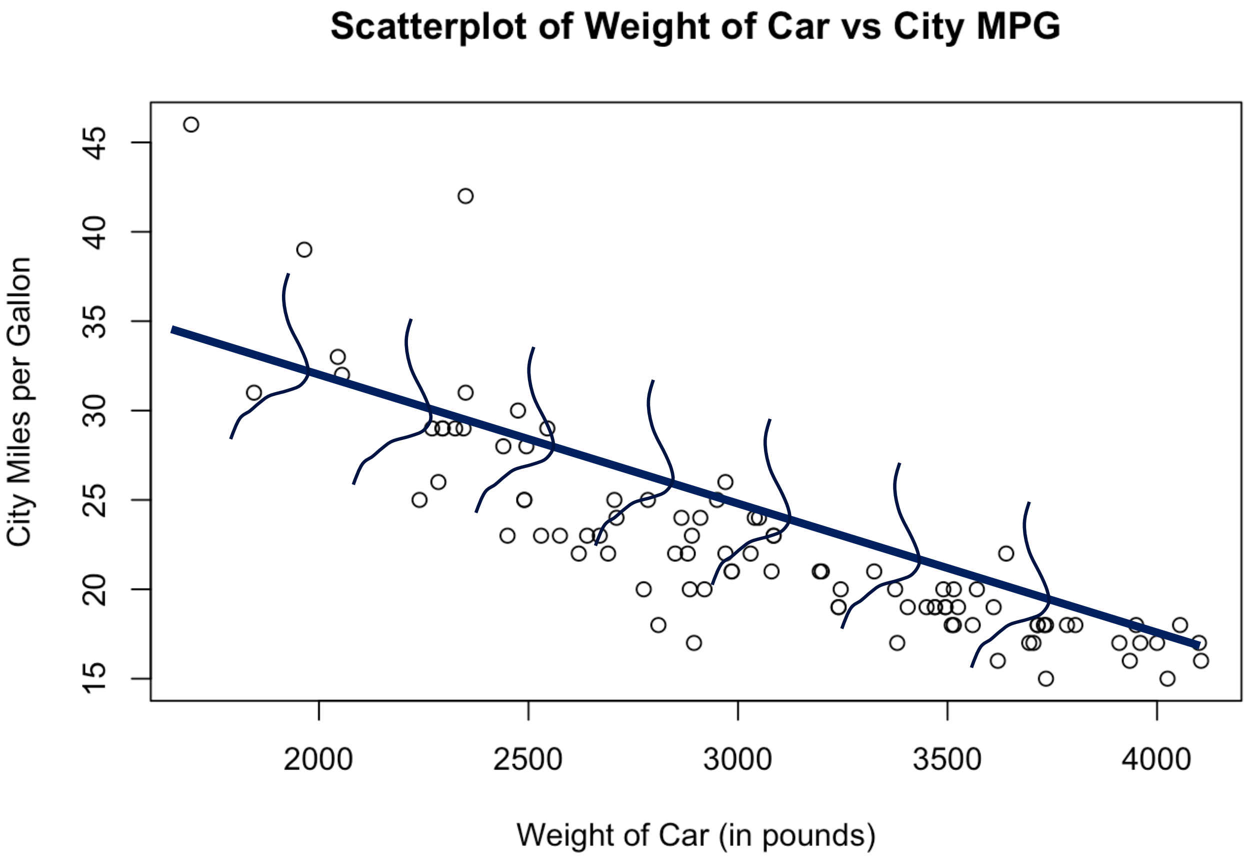
# Linear Regression: Gauss Markov Assumptions

- ‘Spherical’ errors
- The errors should be normally distributed about the regression line
- If skewed, this means that the regression line is not ‘splitting’ the data, and is thus biased



# Linear Regression:
# Gauss Markov Assumptions

- ‘Spherical’ errors
- With more than a single IV, we need to conceptualize this in three dimensions
- A circle in three dimensions is a sphere
  - 68/95/99 of the error distribution



# Linear Regression: $R^2$

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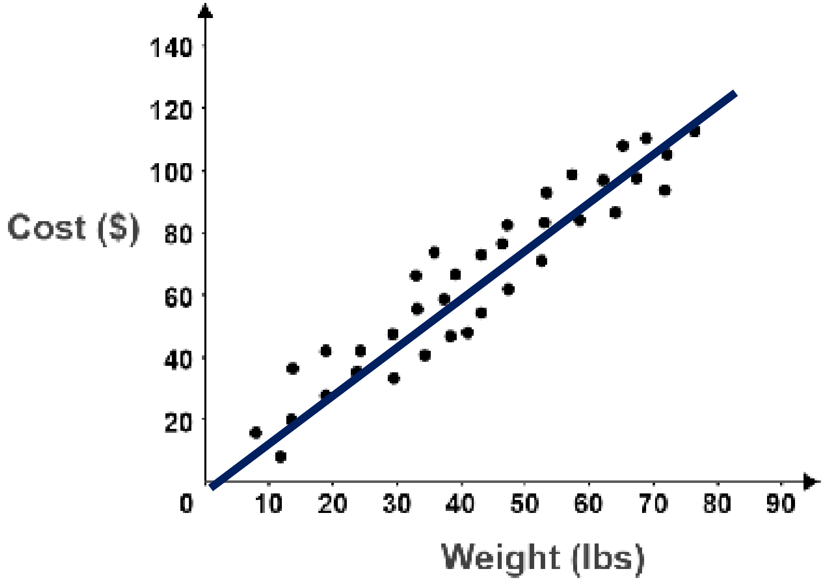
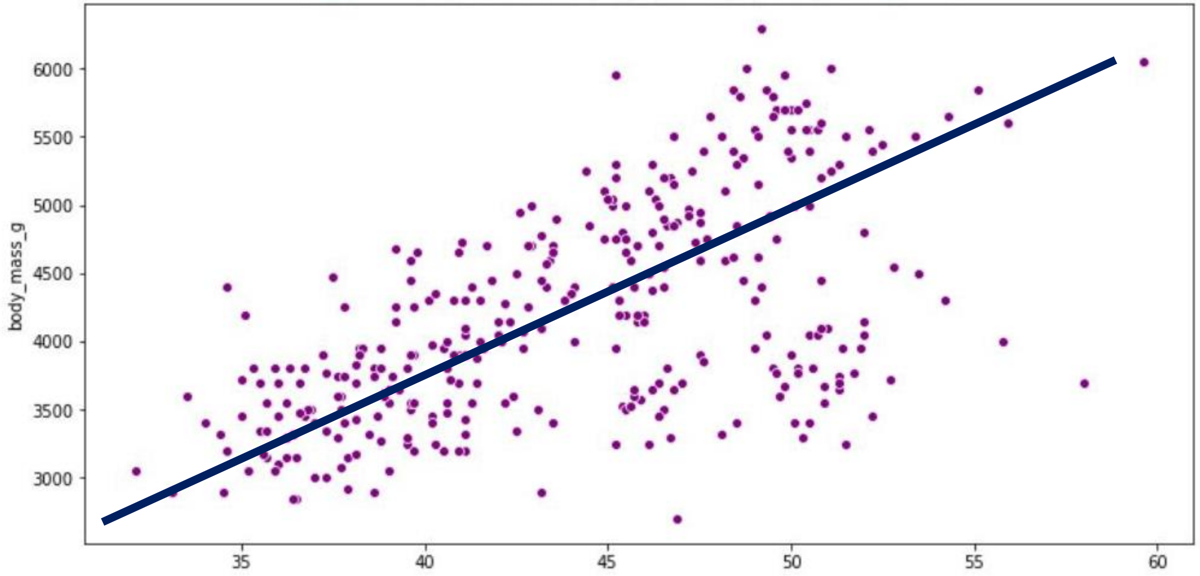
- How do we know if the linear regression line is doing a ‘good’ job in predicting the observed data
- Such a measure is inherently contingent on the dispersion of the observed data – the variance of the data



# Linear Regression: $R^2$

- How do we know if the linear regression line is doing a ‘good’ job in predicting the observed data
- Such a measure is inherently contingent on the dispersion of the observed data
- Where there is a greater degree of stochastic and systematic variation at work in the observed data, the linear regression estimator will do the best it can
- We can only reduce such variation to a limited degree

# Linear Regression: $R^2$

- How do we know if the linear regression line is doing a 'good' job in predicting the observed data
- We quantify the degree of variation explained by the linear regression process by the metric of $R^2$ and adjusted $R^2$
- This is also termed the coefficient of determination or "goodness of fit" measure

# Linear Regression: $R^2$

- Total Sum of Squares: the total variation in $Y_i$
- Residual Sum of Squares: the variation in $Y_i$ not explained by $X_i$
- $R^2 = 1 - \frac{RSS}{TSS}$

# Linear Regression: $R^2$

- Total Sum of Squares: $TSS = \Sigma_{i=1}^{n}(y_i - \bar{y})^2$

- Residual Sum of Squares: $RSS = \sum_{i=1}^{n}(\hat{u}_i^2)$

- $R^2 = 1 - \frac{RSS}{TSS}$

# Linear Regression: $R^2$

- As we can see from these equations, there is no way to quantify how many independent variables are being used
  - If you add more independent variables, you will explain more of the observed variation
- $TSS = \Sigma_{i=1}^{n}(y_i - \bar{y})^2$
- $RSS = \sum_{i=1}^{n}(\hat{u}_i^2)$
- $R^2 = 1 - \frac{RSS}{TSS}$

# Linear Regression: $R^2$

- As we can see from these equations, there is no way to quantify how many independent variables are being used
  - If you add more independent variables, you will explain more of the observed variation
- Thus, we prefer to use adjusted $R^2$
- This weights our measure to account for the number of IVs we're using

$$R^2_{adj} = 1 - \frac{(1 - R^2)(n - 1)}{n - p - 1}$$

$where:$

$R^2 = R - squared$

$n \quad = number\ of\ samples/rows\ in\ the\ data\ set$

$p \quad = number\ of\ predictors/features$

# Linear Regression: Significance

- We've covered how to calculate the linear regression estimates, how uncertainty is modeled, and how well the model explains observed variation in the outcome variable
- What about statistical significance?
- We calculate a t-statistic by comparing observed values to the value posited by the null hypothesis, over the standard error of the model

$$t_{n-k} = \frac{\hat{\beta} - \beta^*}{se(\hat{\beta})}$$

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$$t_{n-k} = \frac{\hat{\beta} - 0}{se(\hat{\beta})}$$

# Linear Regression: Tables

- What does this look like?

Table 1: Effect of Conspiratorial Ideation and Institutional Trust on Predicted COVID-19 Mitigation Behaviors.

| | | | | | | |
|---|---|---|---|---|---|---|
| Conspiratorial Ideation | $-0.518^{***}$ | $-0.465^{***}$ | | | | |
| | [0.062] | [0.086] | | | | |
| Institutional Trust: State | | | $0.182^{***}$ | $0.176^{***}$ | | |
| | | | [0.047] | (0.057) | | |
| Institutional Trust: Federal | | | | | $0.288^{***}$ | $0.301^{***}$ |
| | | | | | [0.040] | (0.051) |
| Female | | 0.196 | | 0.088 | | 0.134 |
| | | [0.134] | | (0.134) | | (0.123) |
| Age | | 0.070 | | 0.130 | | 0.115 |
| | | [0.088] | | (0.092) | | (0.084) |
| Income | | −0.095 | | −0.069 | | −0.044 |
| | | [0.084] | | (0.089) | | (0.082) |
| Education | | −0.044 | | −0.037 | | −0.146 |
| | | [0.110] | | (0.109) | | (0.101) |
| Ideology | | −0.064 | | $-0.155^{***}$ | | −0.058 |
| | | [0.042] | | (0.049) | | (0.048) |
| Person of Color | | −0.100 | | −0.091 | | 0.015 |
| | | [0.182] | | (0.207) | | (0.189) |
| COVID-19 Personal Experience | | −0.055 | | −0.097 | | −0.045 |
| | | [0.086] | | (0.097) | | (0.090) |
| Constant | $1.345^{***}$ | $1.819^{***}$ | $-0.542^{***}$ | 0.395 | $-0.839^{***}$ | −0.360 |
| | [0.155] | [0.649] | [0.180] | (0.640) | [0.150] | (0.605) |
| N | 177 | 137 | 280 | 134 | 281 | 134 |
| Adjusted $R^2$ | 0.250 | 0.211 | 0.060 | 0.101 | 0.184 | 0.242 |

*Note.* Values presented are linear regression estimates. Dependent variable is predicted COVID-19 behaviors - coded such that higher values indicate a higher likelihood of behaving in line with scientific recommendations for COVID-19 transmission mitigation. Gender and race are dummy variables coded such that 1 denotes female and person of color respectively. Standard errors in parentheses. Efron (1982) variant standard errors in brackets. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

# Linear Regression: Tables

Table 1: Effect of Conspiratorial Ideation and Institutional Trust on Predicted COVID-19 Mitigation Behaviors.

Independent Variables

| | | | | | | |
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| | | | [0.047] | (0.057) | | |
| Institutional Trust: Federal | | | | | 0.288*** | 0.301*** |
| | | | | | [0.040] | (0.051) |
| Female | | 0.196 | | 0.088 | | 0.134 |
| | | [0.134] | | (0.134) | | (0.123) |
| Age | | 0.070 | | 0.130 | | 0.115 |
| | | [0.088] | | (0.092) | | (0.084) |
| Income | | −0.095 | | −0.069 | | −0.044 |
| | | [0.084] | | (0.089) | | (0.082) |
| Education | | −0.044 | | −0.037 | | −0.146 |

Models

| | | | | | | |
|---|---|---|---|---|---|---|
| | | [0.110] | | (0.109) | | (0.101) |
| Ideology | | −0.064 | | −0.155*** | | −0.058 |
| | | [0.042] | | (0.049) | | (0.048) |
| Person of Color | | −0.100 | | −0.091 | | 0.015 |
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| | | [0.086] | | (0.097) | | (0.090) |
| Constant | 1.345*** | 1.819*** | −0.542*** | 0.395 | −0.839*** | −0.360 |
| | [0.155] | [0.649] | [0.180] | (0.640) | [0.150] | (0.605) |
| N | 177 | [illegible] | 280 | 134 | 281 | 134 |
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# Linear Regression: Multiple IVs

- We state the linear regression equation as:

$$y_i = \hat{\alpha} + \hat{\beta} x_i + \hat{u}_i$$

- It is important to note that this is functionally shorthand
- In the single IV case, $x_i$ is a vector
- This equation works for multiple IVs as well

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$$y_i = \hat{\alpha} + \hat{\beta}_1 x_{1i} + \hat{\beta}_2 x_{2i} + \hat{\beta}_3 x_{3i} + \cdots + \hat{u}_i$$

# Linear Regression: Multiple IVs

| $y_i$ | $\hat{\beta}_1$ | $x_{1i}$ |
|---|---|---|
| 1.2 | 1.2 | 1 |
| 2.4 | 1.2 | 2 |
| 3.6 | 1.2 | 3 |
| 4.8 | 1.2 | 4 |
| 6.0 | 1.2 | 5 |
| 7.2 | 1.2 | 6 |
| 8.4 | 1.2 | 7 |
| 9.6 | 1.2 | 8 |
| 10.8 | 1.2 | 9 |
| 12 | 1.2 | 10 |

# Linear Regression: Multiple IVs

| $y_i$ | $\hat{\beta}_1$ | $x_{1i}$ | $\hat{\beta}_2$ | $x_{2i}$ |
|---|---|---|---|---|
| -0.8 | 1.2 | 1 | -2 | 1 |
| -1.6 | 1.2 | 2 | -2 | 2 |
| -2.4 | 1.2 | 3 | -2 | 3 |
| -3.2 | 1.2 | 4 | -2 | 4 |
| -4 | 1.2 | 5 | -2 | 5 |
| -4.8 | 1.2 | 6 | -2 | 6 |
| -5.6 | 1.2 | 7 | -2 | 7 |
| -6.4 | 1.2 | 8 | -2 | 8 |
| -7.2 | 1.2 | 9 | -2 | 9 |
| -8 | 1.2 | 10 | -2 | 10 |

# Linear Regression: Multiple IVs

| $y_i$ | $\hat{\beta}_1$ | $x_{1i}$ | $\hat{\beta}_2$ | $x_{2i}$ | $\hat{\beta}_3$ | $x_{3i}$ |
|---|---|---|---|---|---|---|
| -0.3 | 1.2 | 1 | -2 | 1 | 0.5 | 1 |
| -0.6 | 1.2 | 2 | -2 | 2 | 0.5 | 2 |
| -0.9 | 1.2 | 3 | -2 | 3 | 0.5 | 3 |
| -1.2 | 1.2 | 4 | -2 | 4 | 0.5 | 4 |
| -1.5 | 1.2 | 5 | -2 | 5 | 0.5 | 5 |
| -1.8 | 1.2 | 6 | -2 | 6 | 0.5 | 6 |
| -2.1 | 1.2 | 7 | -2 | 7 | 0.5 | 7 |
| -2.4 | 1.2 | 8 | -2 | 8 | 0.5 | 8 |
| -2.7 | 1.2 | 9 | -2 | 9 | 0.5 | 9 |
| -3 | 1.2 | 10 | -2 | 10 | 0.5 | 10 |

# Let’s Try an Example Together

- Data from 2012 ANES
- Effect of SES on Party Identification
- Think about your data structure, and how this would apply as we go through this example

# Linear Regression: Multiple IVs

- Multiple IVs complicate matters in two key ways
- First, the IVs may be correlated with each other violating one of the GM assumptions
- Second, the model is less capable of assigning the variance in outcomes due to one IV over another
- This issue increases exponentially, not linearly, with the addition of more and more Ivs

# Linear Regression: Conclusion

- We know how to:
  - Calculate the linear best fit line (regression coefficient and constant)
  - Calculate uncertainty about the regression line
  - Calculate the coefficient of determination
  - **Interpret linear regression results**
- Remember: linear regression requires a continuous DV and a number of assumptions to function properly
- **With observational data, regression cannot make causal claims**

# For Next Class

- Read the excerpt on iCollege for Thursday
- Complete Final Paper and submit by Thursday (7/28) by midnight